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People-Value at Risk:
A Key Indicator for Sound Management

José Manuel Feria Domínguez

Enrique Jiménez Rodríguez

Pilar Camacho Rubio

Pablo de Olavide University

Department of Financial Economics and Accounting

Carretera de Utrera, km. 1

41013 Seville (Spain)

(jmferdom@upo.es; ejjimrod@upo.es; pcamacho@upo.es)

DEPARTMENT OF FINANCIAL ECONOMICS AND ACCOUNTING

PEOPLE-VALUE AT RISK: A KEY INDICATOR FOR SOUND MANAGEMENT

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José Manuel Feria Domínguez (*corresponding author*)
Universidad Pablo de Olavide
Department of Financial Economics and Accounting
Carretera de Utrera, km. 1 - 41013 Seville (Spain)
Phone +34 954 349 363; fax: +34 954 348 353
Email: jmferdom@upo.es

Enrique Jiménez Rodríguez
Universidad Pablo de Olavide
Department of Financial Economics and Accounting
Carretera de Utrera, km. 1 - 41013 Seville (Spain)
Phone +34 954 977 925; fax: +34 954 348 353
Email : ejjimrod@upo.es

Pilar Camacho Rubio
Universidad Pablo de Olavide
Department of Financial Economics and Accounting
Carretera de Utrera, km. 1 - 41013 Seville (Spain)
Email: pcamacho@upo.es

Abstract

People are the most important asset for companies, but they are also a source of risk. People risk involves both intentional and unintentional people's behavior that could provoke losses for firms. The main goal of this paper is twofold: to identify four different risk categories (Internal Fraud, Employment Practices and Workplace Safety, Clients, Products and Business Practices and Execution, Delivery & Process Management) that are "people-related", and to measure the people risk exposure by applying the concept of People-Value at Risk (People-VaR) as a new key-indicator for sound management in the financial sector. Then, we also calculate the Risk Adjusted Return on Capital (RAROC) to evaluate the bank's risk-adjusted performance, being both measures useful tools for monitoring the shareholder's value creation.

Keywords: People Risk, People-Value at Risk, Risk Adjusted return on Capital (RAROC), Banking performance

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A KEY INDICATOR FOR SOUND MANAGEMENT

1. Introduction

People are considered to be the most important asset for firms as well as a critical resource for creating competitive advantage (Pfeffer, 1998). Jackson and Schuler (2003) states they are potential contributors to the creation and realization of the organization's mission, vision, strategy and goals. But, on the contrary, people are also a key source of risk rooted in the underlying competencies, attitudes, motivation, commitment and honesty of the employees, resulting in a complex task for managers.

In the financial discipline, people risk is an interesting field to explore since this topic has received little attention by risk managers, supervisors and regulators who have mainly focused on measuring, controlling and managing traditional financial risk –credit risk, market risk and operational risk– The Basel Committee on Banking Supervision (henceforth, the Committee, 2006) explicitly mentioned "people" as a source of risk when defining operational risk[1]. In particular, Employment Practices and Workplace Safety (henceforth, EPWS) is identified as an event type category to account for "*the potential losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims or from diversity and discrimination events*". Although this is a clear example of people risk, in practice, its boundaries are much wider as it arises not only in the day-to-day operations of individual entities but also in unethical or even illegal activities across the whole industry (MacConnell, 2008). In a broad sense, people risk involves the risk to the firm caused by its people and the risk to the firm caused by what the firm does to its people. More specifically, it regards to the potential deviation

1The risk of loss resulting from inadequate or failed internal processes, *people* and systems or external events.

from their expected behavior within an organization, i.e., the risk that people do not follow the organization's procedures, practices and rules. It can be originated from two main causes depending on the "intention" of the people involved (MacConnell and Blacker, 2011):

- Deliberate deviant behavior that could be *illegal* -an individual's intention to break civil or securities laws, such as theft or insider trading-, *unethical* -intentional behavior that, while not quite illegal, is frowned upon, such as bullying and sexism-, or *inappropriate* -intentionally breaking specific policies of the firm, such as using the firm's facilities for private use-.

- Non-deliberate deviant behavior or human errors. Blacker et al. (2004) argued that a well-trained workforce, supported by good systems and policies, will make fewer mistakes than stressed, unhappy or inexperienced workers.

Following this classification, apart from the abovementioned EPWS, other event type Basel II categories should be included under people risk[2] framework such as:

- Internal Fraud (henceforth, IF) reflects *the losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy such as unauthorized activities, theft and fraud*.

- Clients, Products and Business Practices (henceforth, Clients) which relates to l*osses arising from an unintentional or negligent failure to meet a professional obligation to specific clients, or from the nature or design of a product*.

2 We exclude other even type categories such as External Fraud, Damage to Physical Assets and Business Disruption and System Failures.

- Execution, Delivery & Process Management (henceforth, Processes) accounts for *losses from failed transaction processing or process management, from relations with trade counterparties and vendors.*

The main objective of this paper is to quantify the people risk by providing a new key-indicator for managers of financial institutions to improve bank's risk-adjusted performance. For this purpose, we apply the Value at Risk (Jorion, 1997; Dowd, 1998), concept to the aggregate loss distribution for each particular event type described above (EPWS, IF, Clients and Processes) in order to obtain a holistic measure called *People-Value at Risk* (henceforth, People-VaR). This statistical measure is then used for estimating the Risk Adjusted Return on Capital (RAROC) as a benchmark for the financial performance in the financial sector. Based on the above measures, in this study, we identify and quantify the necessary people capital return for value creation.

The paper is structured as follows. Section 2 describes the methodological framework. Section 3 analyzes de data and sample. The Sections 4 and 5 summarizes the most important results and conclusions.

2. Methodological Framework

People Risk Measurement –in terms of economic capital[3]– is a challenging task for managers. Losses derived from people can also be broken down into expected loss (EL) and unexpected loss (UL). Thus, the set of expected losses will cover all those foreseeable losses that are intrinsic to the ordinary activity of the entity. Therefore, if they are seen as

3 Regulatory capital represents the level of equity to cover possible losses arising from different types of risks, . In turn, Economic capital concept is that the regulatory minimum level of solvency is set by the supervisor, while in economic equity level desired rating relates to a goal set by the institution.

representing just one more cost for the business, they should be included implicitly in the final price of the products and services, or even provisioned.

One example, fairly typical of this type of loss, would be the “cash differences”, recorded almost every day in banking offices, but generally of trivial amounts. On the other hand, unexpected losses refer to events not initially foreseen by the entity that may, however, give rise to huge losses for the institution due to the magnitude of the potential damage. In the first instance, the Basel Committee suggests that such losses should be covered by regulatory capital.

Independently of whether or not the loss is foreseen, it is essential to define two parameters at the time of identifying it: firstly, the severity, or monetary amount of the loss; and, secondly, the frequency with which the event is repeated during a specified period of time, that is, the probability that the event may occurs. In so far as both variables are assumed to be statistically independent, they are modeled separately. In general terms, in the historical set collection of financial entity’s losses, a large number of events will be recorded that cause losses of small magnitude, such as the "cash differences" already mentioned, for example.

The Loss Distribution Approach (LDA) is a statistical technique, inherited from the actuarial field (see Bühlmann, 1970), the objective of which is to obtain a probability distribution of aggregated losses. The model is constructed from the information of historical losses from which we must estimate the distribution of both the frequency and the severity. Once these have been defined, the next step is to obtain the distribution of aggregate losses due to people risk. For the calculation of the economic capital, the concept of Value at Risk (VaR) is applied to the context of the operational risk, adopting the nomenclature of People Value at Risk. Since People-VaR is a statistical measure which represents a percentile of the distribution of losses, it requires the establishment of certain parameters:

- A confidence interval associated with the calculation. In terms of capital regulatory, the Basel Committee (2006: 151) is explicit in setting 99.9% for this. From a managerial point of view 95% could be also applied.

- A period of time to which the estimation will refer. With regard to people risk, the estimation is calculated for one year time.

- A currency of reference. The People-VaR is expressed in monetary units. In consequence, this variable becomes an intuitive and easily-understandable magnitude for its potential users (regulators, supervisors, risk managers, etc.) who will then be able to take their corresponding decisions.

- A hypothesis on the distribution of the variable analyzed. The Basel Committee (2001: 34) proposed the Lognormal distribution for dealing with the severity, and the Poisson distribution for the frequency. However, the distributions ultimately selected should be those that best fit the historical pattern of losses observed in an entity, and the nature of these losses can obviously be very different from that of other entities.

In short, we can interpret the People-VaR as a figure, expressed in monetary units, that informs us about the maximum potential loss that an entity could incur due to people risk during a time horizon of one year, and with a given level of statistical confidence. Under the assumption that the severities are independent of each other, and that these, in turn, are independent of the frequencies, in each category, the next step consists of modeling separately these two variables.

2.1. *Fitting the Frequency Distribution*

The random variable N will symbolise the number of events occurring in a time horizon (T) of one year; with a probability function p. This discrete variable represents the frequency of losses, whose distribution function, $P(n)$, is expressed as:

$$\mathrm{P}(n) = \sum_{k=0}^{n} p(k) \tag{1}$$

According to authors such as Frachot et al. (2006) and Mignola and Ugoccioni (2005), the Poisson distribution –utilized successfully in actuarial techniques for insurance– is an option offering many advantages for the modeling of frequency. This function is characterized by one single parameter, lambda (λ), which represents, on average, the number of events occurring in one year. This discrete function assumes equi-dispersion between mean and variance, i.e., $E[Y] = Var[Y]$. However, in the operational risk context, the variance usually exceeds the mean, giving rise to the over-dispersion effect (McNeil et al., 2005; Dahen and Dionne, 2010). If over-dispersion arises, the real variance of the sample can be underestimated. Lindsey (1995) proposes the application of the Variance-to-Mean ratio as an indicator of the potential extra Poisson variance. It can be defined as follows: $VtM = \sigma^2 / \mu$. If equi-dispersion holds, this ratio should be equal to one. Potential deviations from this value would imply that the empirical distribution does not follow the Poisson model; that is, if the ratio is higher than one that implies the existence of over-dispersion –or under-dispersion, on the contrary–. Depending on the magnitude of the ratio, the presence or such effects will be more evident. In this sense, Cameron and Trivedi (1998) states that: *"If the sample variance is more than twice the sample mean, then data are likely to remain over-dispersed*". Da Costa (2004) recommends the application of the Binomial model if under-dispersion arises, the Poisson distribution for equi-dispersed scenarios and the Negative Binomial function when over-dispersion is observed. Moscadelli (2005) demonstrates the better fit provided by the Negative Binomial (NB) distribution, which consists of a Poisson function with Gamma distributed parameter.

$$N \sim NB(r,p) \rightarrow P(N=k) = \binom{k+r-1}{k} p^k (1-p)^r \qquad r>0, p \in (0,1) \qquad (2)$$

2.2. *Fitting the Severity Distribution*

Having defined the frequency, we then specify the random variable that represents the amount of loss, henceforth, severity, as *X*, with *F* being its probability function. Thus, the parameters of this probabilistic distribution that best match the data observed will have to be determined. For this task, as already mentioned above, the Committee (2001: 34) first proposed the Lognormal distribution; although there are several parametric distributions that may be valid for such an approach. Thus, Fontnouvelle et al. (2004) include the Pareto; Böcker and Klüppelberg (2005) propose the Weibull; and Mignola and Ugoccioni (2006) add to these the Burr function of distribution as an alternative for modeling the severity, in addition to those cited.

$$X \sim LN(\mu,\sigma) \rightarrow f(x) = \frac{1}{x\sigma\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^2\right] \mu \in \mathbb{R}, \sigma > 0 \qquad (3)$$

The specific values of the parameters of each distribution are estimated by Maximum Likelihood (ML). For this purpose, we apply various statistical tests to calibrate the Goodness of Fit (GOF). Following Chernobai et al. (2006), the statistical test is symbolised by a null hypothesis, H_0: the observed distribution of operational losses, $F(x)$, is fitted to the theoretical distribution, $\hat{F}(x)$; and an alternative hypothesis, H_A, which rejects the former:

$$H_0 : F_n(x) = \hat{F}(x) \qquad H_A : F_n(x) \neq \hat{F}(x) \tag{4}$$

To perform this inferential analysis, we can take support from the following statistical tests: Kolmogorov–Smirnov (K-S) and χ^2 test.

2.3. *Obtaining the Aggregate Loss Distribution (LDA)*

As we have already noted, the severity is a continuous variable whereas the frequency only takes discrete values. Consequently, for the purposes of obtaining the distribution of Aggregate Losses from each of these distributions, we first need to convert the severity into discrete values (Panjer, 2006: 411). Once the distributions of severity and frequency have been characterised and homogenised, the last step of the methodological procedure consists in obtaining the distribution of aggregate losses. Thus, the total loss associated with a type of risk:

$$L(i) = \sum_{n=0}^{N(i)} X_n(i) \tag{5}$$

This amount is therefore what is computed from a random number of loss events, with values that are also random, under the assumption that the severities are independent of each other and, at the same time, independent of the frequency (Frachot et al., 2005: 2). The distribution function of the variable $L(i)$ –$G_i(x)$– is obtained by:

$$G_i(x) = \begin{cases} \sum_{n=1}^{\infty} p_i(n) F_i^{n*}(x) & x > 0 \\ p_i(0) & x = 0 \end{cases} \tag{6}$$

The asterisk denotes the convolution[4] in the function F, where F^{n*} is n-times the convolution of F with itself, that is:

$$\begin{aligned} F^{1*} &= F \\ F^{n*} &= F^{(n-1)*} * F \end{aligned} \tag{7}$$

To obtain the aggregate loss function G(x), we apply the Fast Fourier Transforms (FFT) (see Panjer, 2006).

2.4. *People Value at Risk*

Once the aggregate distribution function has been determined, all that remains to calculate the regulatory capital associated with each event type is to apply the concept of Value at Risk (VaR), that is, to calculate the 99.9% percentile of such distribution. In a strict sense, as warned by the Committee (2006: 151), the Economic Capital (Capital at Risk, CaR) should cover, a priori, only the unexpected loss (UL):

$$CaR = UL(i;\alpha) \tag{8}$$

However, if the entity does not demonstrate, in a suitable way, that the expected loss has been covered, in a broader sense, the regulatory capital should be considered as being computed to cover both types of loss; in such case, the CaR and VaR are identical.

$$\begin{aligned} CaR \equiv VaR(i;\alpha) &= G_i^{-1}(\alpha) \\ &= EL(i) + UL(i;\alpha) \end{aligned} \tag{9}$$

Mathematically, the expected loss can be defined as:

$$EL(i) = E[L(i)] = \int_0^\infty x d\mathrm{G}_i(x) = E[X(i)] \text{ x } E[N(i)] \tag{10}$$

4 The convolution is a mathematical procedure that transforms the distributions of frequency and severity into a third distribution (LDA) by the superposition of the two (see Feller, 1971:143).

Consequently, the unexpected loss would be expressed as follows:

$$\mathrm{UL}(i;\alpha) = \mathrm{G}_i^{-1}(\alpha) - E[L(i)] = \inf\{x | \mathrm{G}_i(x) \geq \alpha\} - \int_0^\infty x d\mathrm{G}_i(x) \tag{11}$$

Assuming perfect dependence between the risks associated with the people, People Value at Risk merely consists of the aggregation of the individual CaR's corresponding to each risk; that is:

$$PeopleVaR(\alpha) = \sum CaR_i(\alpha) \tag{12}$$

2.5. *Economic Capital and RAROC*

When assessing the performance of a business, it is essential to determine both its expected return and the risk embodied. For this purpose, RAROC (Risk Adjusted Return on Capital) models are widely used for providing measures of risk-adjusted returns. These methodologies allow setting minimum prices adjusted to the risk emanating from the business. RAROC models are intrinsically linked to the concept of economic capital, i.e., the amount of equity required to maintain a solvency target rating in the financial institution. In other words, it represents the amount of money that, given a certain probability and a time period, safeguards the financial institution from a possible bankruptcy. The basic equation (see equation 13) is relatively simple: return divided by capital. If internal data is available, the business return is obtained just using arithmetic. Instead, the determination of required capital implies greater complexity. To do this, the organization must identify what risks face at (market risk, credit risk, operational risk, liquidity risk, etc.) and quantified them, as accurately as possible, in order to get a more realistic model.

$$RAROC = \frac{\text{Return People Capital - EL}}{\text{PeopleVaR}} \tag{13}$$

After quantifying the RAROC, this figure is then contrasted against some representative measure of the cost of capital; so, the value creation for shareholders will arise whenever RAROC exceeds the cost of capital.

3. Data and Sample

This study is based on a sample extracted from the AlgoOpdata, an operational losses database provided by Algorithmics-Fitch Group. Of the total sample of the financial sector, we have focused on those events whose risk factor is people. In Table 1, we detail the selected event types.

Table 1: People Risk

Internal fraud	
Unauthorised Activity	Transactions not reported (intentional) Transaction type unauthorised (w/monetary loss) Mismarking of position (intentional)
Theft and Fraud	Fraud / credit fraud / worthless deposits Theft / extortion / embezzlement / robbery Misappropriation of assets Malicious destruction of assets Forgery Check kiting Smuggling Account take-over / impersonation / etc. Tax non-compliance / evasion (wilful) Bribes / kickbacks Insider trading (not on firm's account)
Employment Practices and Workplace Safety	
Employee Relations	Compensation, benefit, termination issues Organised labour activity
Safe Environment	General liability (slip and fall, etc.) Employee health & safety rules events Workers compensation
Clients, Products & Business Practices	
Suitability, Disclosure & Fiduciary	Fiduciary breaches / guideline violations Suitability / disclosure issues (KYC, etc.) Retail customer disclosure violations Breach of privacy Aggressive sales Account churning Misuse of confidential information Lender liability
Improper Business or Market Practices	Antitrust Improper trade / market practices Market manipulation Insider trading (on firm's account) Unlicensed activity Money laundering
Selection, Sponsorship & Exposure	Failure to investigate client per guidelines Exceeding client exposure limits
Advisory Activities	Disputes over performance of advisory

	activities
Execution, Delivery & Process Management	
Transaction Capture, Execution & Maintenance	Miscommunication Data entry, maintenance or loading error Missed deadline or responsibility Model / system misoperation Accounting error / entity attribution error Other task misperformance Delivery failure Collateral management failure Reference Data Maintenance
Monitoring and Reporting	Failed mandatory reporting obligation Inaccurate external report (loss incurred)
Customer Intake and Documentation	Client permissions / disclaimers missing Legal documents missing / incomplete
Customer / Client Account Management	Unapproved access given to accounts Incorrect client records (loss incurred) Negligent loss or damage of client assets
Trade Counterparties	Non-client counterparty misperformance Misc. non-client counterparty disputes

The AlgoOpdata contains worldwide operational risk events from 1972 to 2009. The risk events are collected from a variety of sources including: regulatory reports, court and legal documents, consulting company reports and business publications. The database tracks pure operational risk events indexed by the Basel Committee. To qualify as an AlgoOpData event, it must be closed and settled. The loss must be quantifiable and the loss amount threshold is set in USD one million or more –or the equivalent in another currency– at the time the loss is made public. Exchange rates are tagged to settlement date for loss amounts that are reported in non-USD denominations. Inflation is also considered, so the United States Consumer Price Index (CPI) data is used to obtain the current value of the USD Loss amount. In this paper, we focus exclusively on the financial services sector. For convenience, we select a temporary window between 1994 and 2009. This is because the frequency of previous period is not statistically significant.In summary, our sample consists of 1,027 people risk events recorded during the last sixteen years.

Following the regulatory guidelines, we use an annual risk horizon in the configuration of the LDA model. In this sense, the dataset used consists of sixteen years of historical losses and, therefore, with sixteen observations for the frequency. The first step in our methodological process is to estimate the mean and variance of the frequency distribution for each event type. From observing table 2, the Variance-to-Mean (VtM) ratio is higher than one in all of the event types. But, according to Cameron and Trivedi (1998) the over-dispersion is considered to be significant for those event types where the variance is more than twice the mean. Applying this rule, most of the risk event types are considered over-dispersed; except the EP&WS whose VtM ratio is (1.58), middle way between 1 and 2. For this particular case, since variance is slightly higher than mean, we also assume the over-dispersed behavior, fo which the Negative Binomial distribution is recommended (Da Costa ,2004) .

Regarding the severity, it should be noted that the mean is, in all the cases, much higher than the median. This fact constitutes a clear sign of the positive asymmetry of the distributions. Taken together, this factor denotes the grouping of distribution body in a range of low severity values. At the same time, the observed values for the shape parameters describe distributions with positive asymmetry and leptokurtosis; however, each risk event type presents a different degree of intensity in both measures. More specifically, on this aspect, the "Clients" has the highest degree of skewness (10.20) and kurtosis (114.99), whereas for EP&WS, the skewness and kurtosis are notably lower (2.81 and 8.31, respectively,). On this point, it should be noted that in the EP&WS category we have observed some features clearly differentiated from the rest: a low degree of asymmetry and kurtosis, and a very moderate over-dispersion. This singular character is due to the small number of observations recorded, in comparison with other sub-sets of the sample.

Table 2: Descriptive Statistics

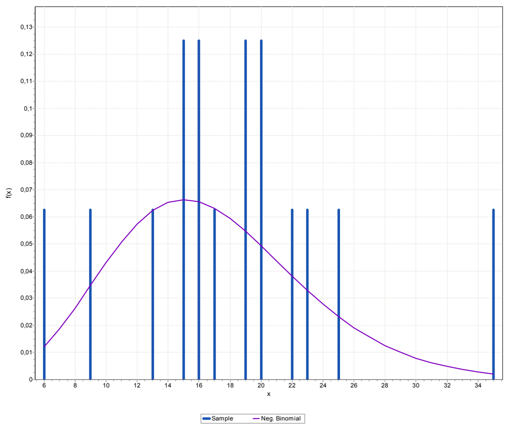
Event type	N	Mean	Median	SD	Skewness	Kurtosis	VtM ratio
INTERNAL FRAUD	290	138.44	13.07	565.69	8.63	90.12	2.45
EP & WS	73	19.16	4.02	33.82	2.81	8.31	1.58
CLIENTS	563	134.86	12.88	667.46	10.20	114.99	10.20
PROCESS	101	49.77	8.58	147.86	5.50	32.77	3.04

4. Results

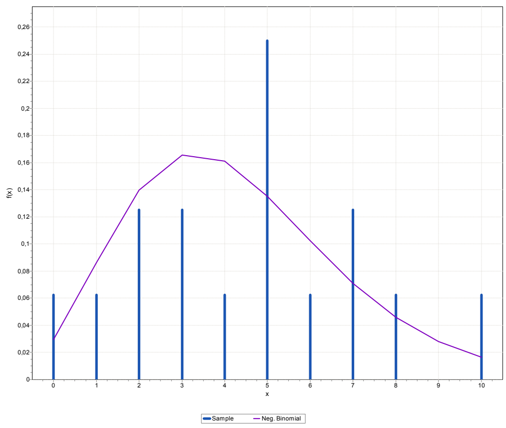
Having proved the existence of over-dispersion in most of the people event types, we assume that Negative-binomial distribution is the most suitable function for modeling the frequency. In Figure 1, the corresponding histograms are illustrated for each particular risk category:

Figure 1: Frequency Histograms

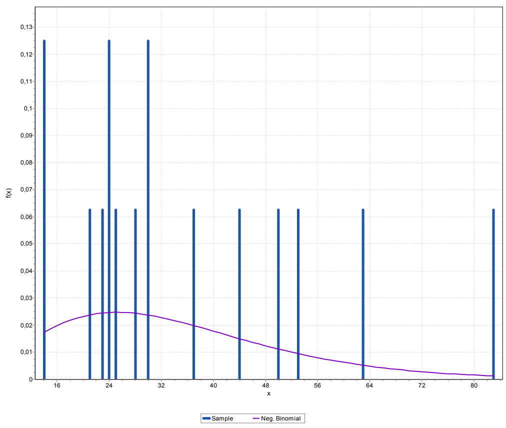
INTERNAL FRAUD



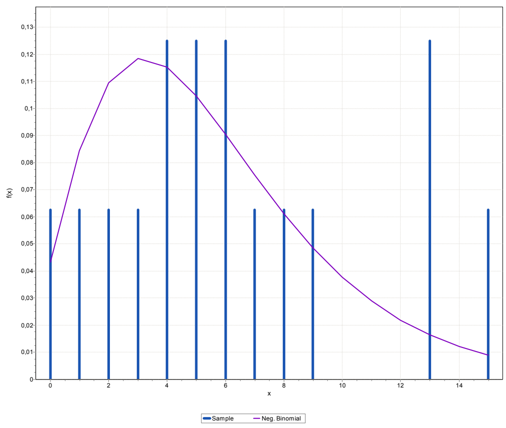
EP & WS



CLIENTS



PROCESS



For fitting the severity distribution we have applied the Kolmogorov-Smirnov test and the Chi-squared test. Table 3and 4 shows the goodness of fit results for severity. According to the Kolmogorov-Smirnov test, the assumption of the lognormal distribution is accepted for all of the even types at 1%. In particular, "Process" provides with a better fit, higher than 5% significance. In turn, when applying the Chi-squared test the Lognormal model gives better results –"Clients" is the only under 5% significance–.

Table 3: Kolmogorov-Smirnov test.

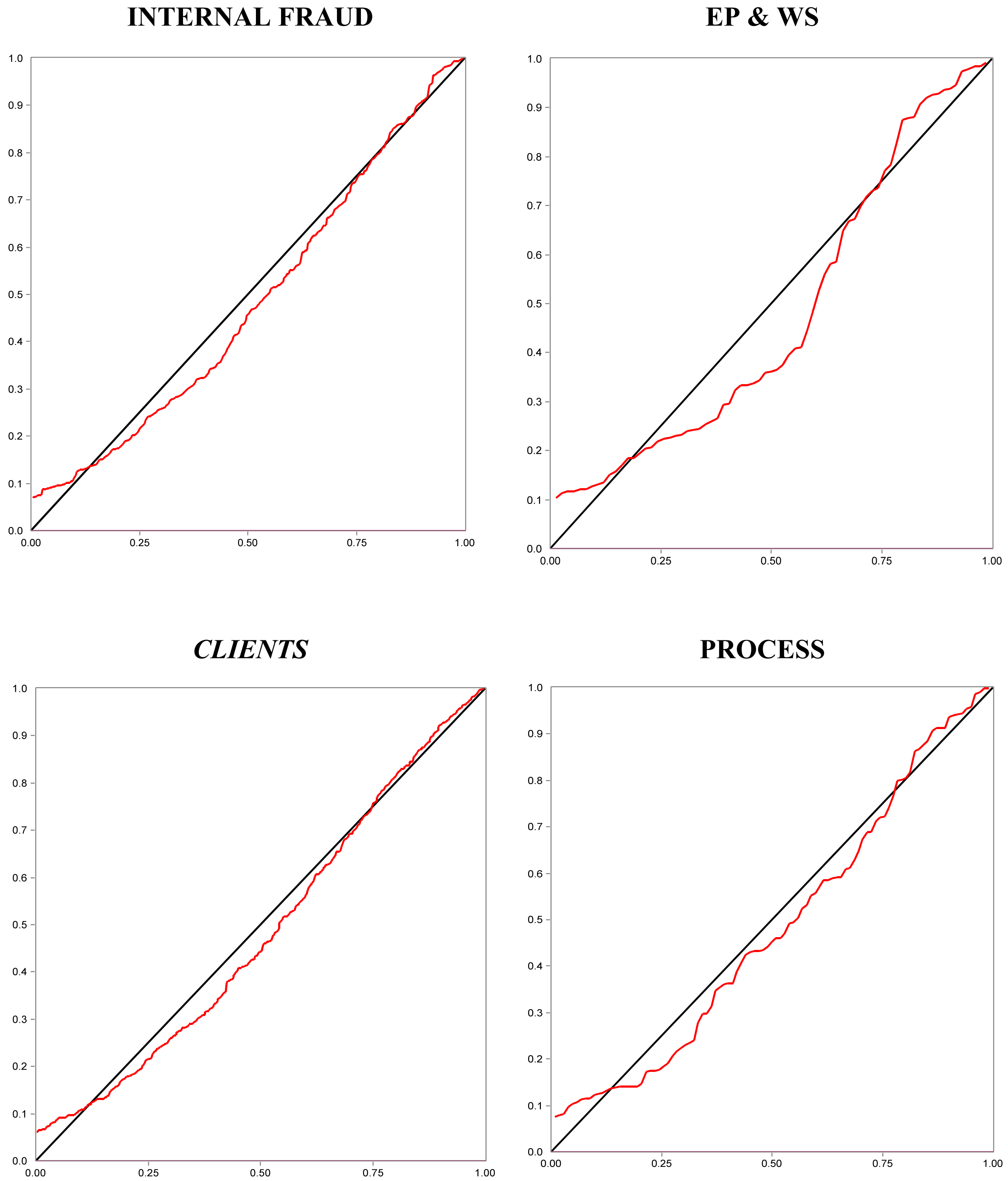
	INTERNAL FRAUD			**EP & WS**			**CLIENTS - PROCESS**			**PROCESS**		
	Critical Value (1-α)			Critical Value (1-α)			Critical Value (1-α)			Critical Value (1-α)		
	90º	95º	99º	90º	95º	99º	90º	95º	99º	90º	95º	99º
	0,0718	0,0797	0,0956	0,1408	0,1565	0,1878	0,0515	0,0572	0,0686	0,1216	0,1351	0,1621
	Statistic (p-value)			**Statistic (p-value)**			**Statistic (p-value)**			**Statistic (p-value)**		
Log-Normal	0,08272 (0,04)			0,16402 (0,03)			0,06902 (0,01)			0,08599 (0,42)		

Table 4: χ^2 test.

	INTERNAL FRAUD			**EP & WS**			**CLIENTS - PROCESS**			**PROCESS**		
	Critical Value (1-α)			Critical Value (1-α)			Critical Value (1-α)			Critical Value (1-α)		
	90º	95º	99º	90º	95º	99º	90º	95º	99º	90º	95º	99º
	13,362	15,507	20,09	7,7794	9,4877	13,277	14,684	16,919	21,666	10,645	12,592	16,812
	Statistic (p-value)			**Statistic (p-value)**			**Statistic (p-value)**			**Statistic (p-value)**		
Log-Normal	9,5479 (0,30)			6,6105 (0,16)			17,352 (0,04)			9,5397 (0,15)		

To reinforce the conclusions obtained from both K-S and Chi-square tests, we have drawn, for each event type, a P-P Plot that shows, comparatively, the theoretical distribution against the empirical one (see Figure 2).

Figure 2: Severity P-P Plots



Once characterized the distributions of frequency (Negative Binomial) and severity (Lognormal), the next step is to determine the aggregate loss distribution. We have chosen the Fast Fourier Transformation (FFT) technique to perform the convolution of both frequency and severity distributions. In particular, for each of the convolutions performed. When the LDA distribution has been determined, the corresponding percentile (People-VaR) is applied as shown in table 5.

Table 5: People-Value at Risk

Event Type	**Log-Normal**		**Neg-Binomial**		**EL**	**VaR**		**CaR**	
	μ	**σ**	**s**	**p**		**95th**	**99,9th**	**95th**	**99,9th**
Internal Fraud	2,7705	1,8647	14	0.431	2,172.00 (9.70)	5,594.02 (24.99)	22,383.40 (100)	3.422,02 (15.29)	20,211.4 (90.30)
EP & WS	1,8843	1,3806	8	0.624	81.07 (10.14)	247.95 (31.03)	799.14 (100)	166,88 (20.88)	718.07 (89.86)
Clients	2,8145	1,8172	5	0.119	4,103.00 (15.47)	9,876.46 (37.25)	26,514.30 (100)	5.773,46 (21.77)	22,411.3 (84.53)
Process	2,3435	1,6033	3	0.312	250,91 (8.15)	829.47 (26.95)	3,077.64 (100)	578,56 (18.80)	2,826.73 (91.85)
People-VaR					6.606,98 (12.52)	16.547,90 (31.36)	52.774,48 (100)	9.940,92 (18.84)	46,167.50 (87.48)

In regulatory terms, the percentile of the distribution of aggregate losses that determines the Capital at Risk is established at 99.9%. For this reason, results have been rescaled, taking as base-value $VaR_{99.9\%}$, to provide a better understanding when comparing different magnitudes. The fact that the Committee has recommended such a high percentile has aroused criticism and a certain apprehension in the banking sector. Given the leptokurtic character of losses, this percentile may lead to an overestimation of the economic capital. However, the intention of the Committee is precisely to cover the risk of possible extreme losses located at the tail. In order to calibrate the impact of the percentile, we have compared the CaR calculated at the 99.9 percentile –henceforth, regulatory CaR– with that obtained by applying a less conservative confidence interval, 95% –henceforth, managerial CaR–. In terms of regulatory CaR, the unexpected loss, i.e., represents around 90% of the base value $VaR_{99.9\%}$; being much higher than the one obtained for the managerial CaR. This fact reveals the conservative effect of the regulatory high percentile on the capital consumption, as reflected in Figures 3 and 4, respectively.

Figure 3: El/Car regulatory Ratio

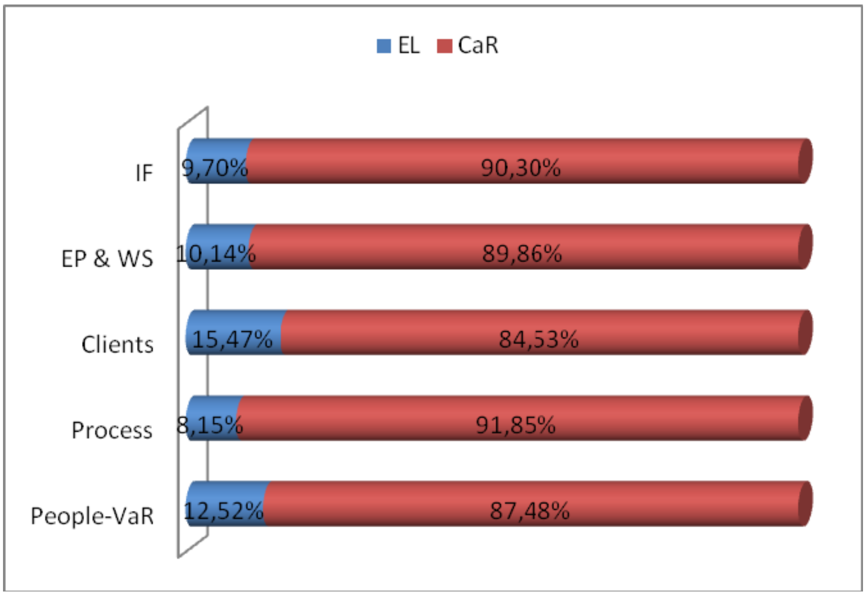
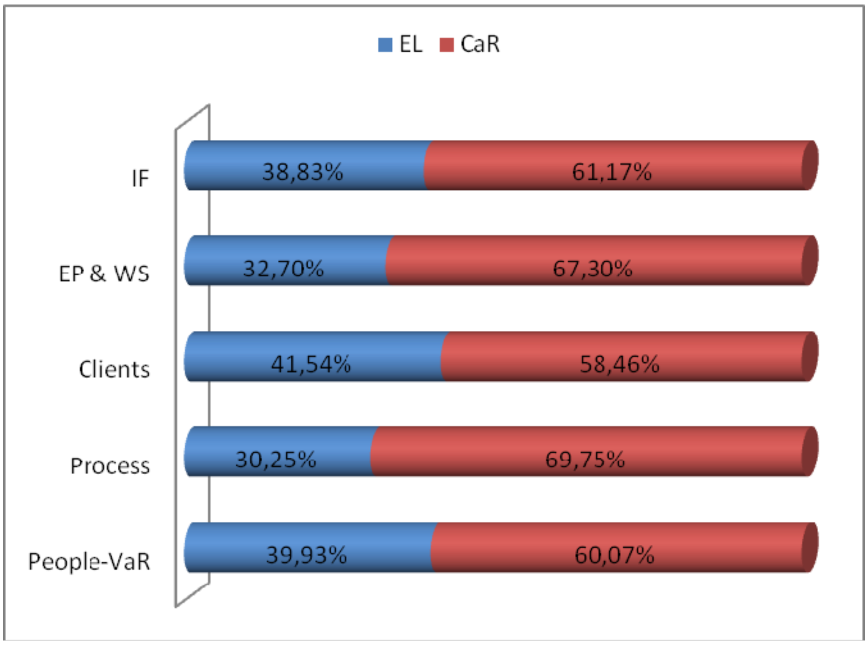
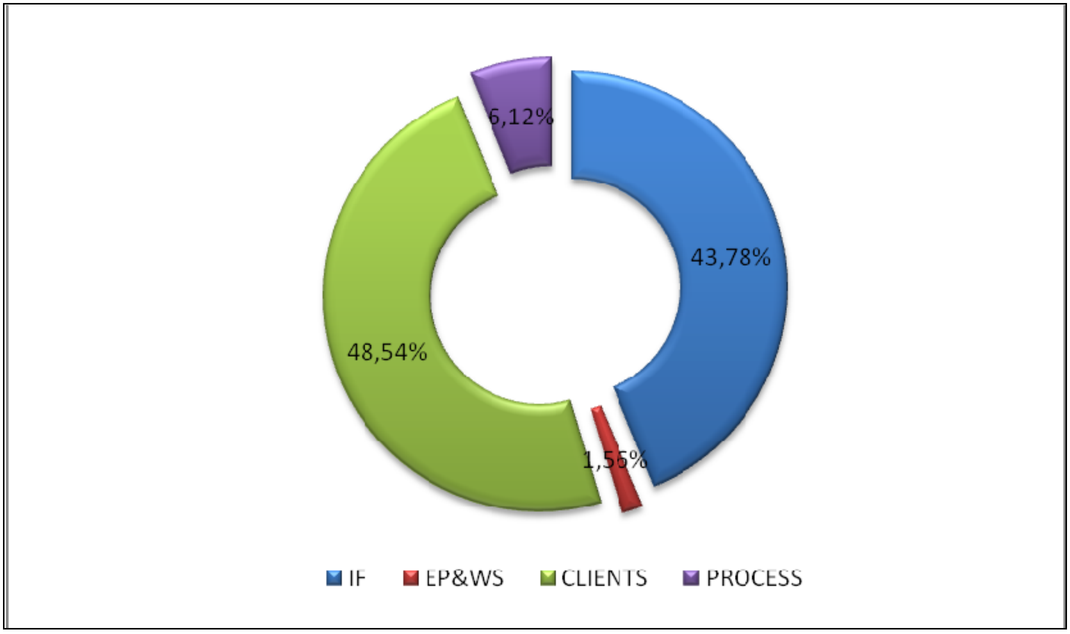


Figure 4: El/Car managerial Ratio



Assuming perfect correlation among the different event types, People-VaR is obtained by aggregation. As figure 5 illustrates, 48.54 % of total People-VaR is due to losses derived from Clients, Products and Business Practices and 43.78% is caused by Internal Fraud events, whereas the rest of categories, that is, Execution, Delivery and Process Management as well as Employment Practices and Workplace Safety are under 8%.

Figure 5: Contribution to People-VaR (%)



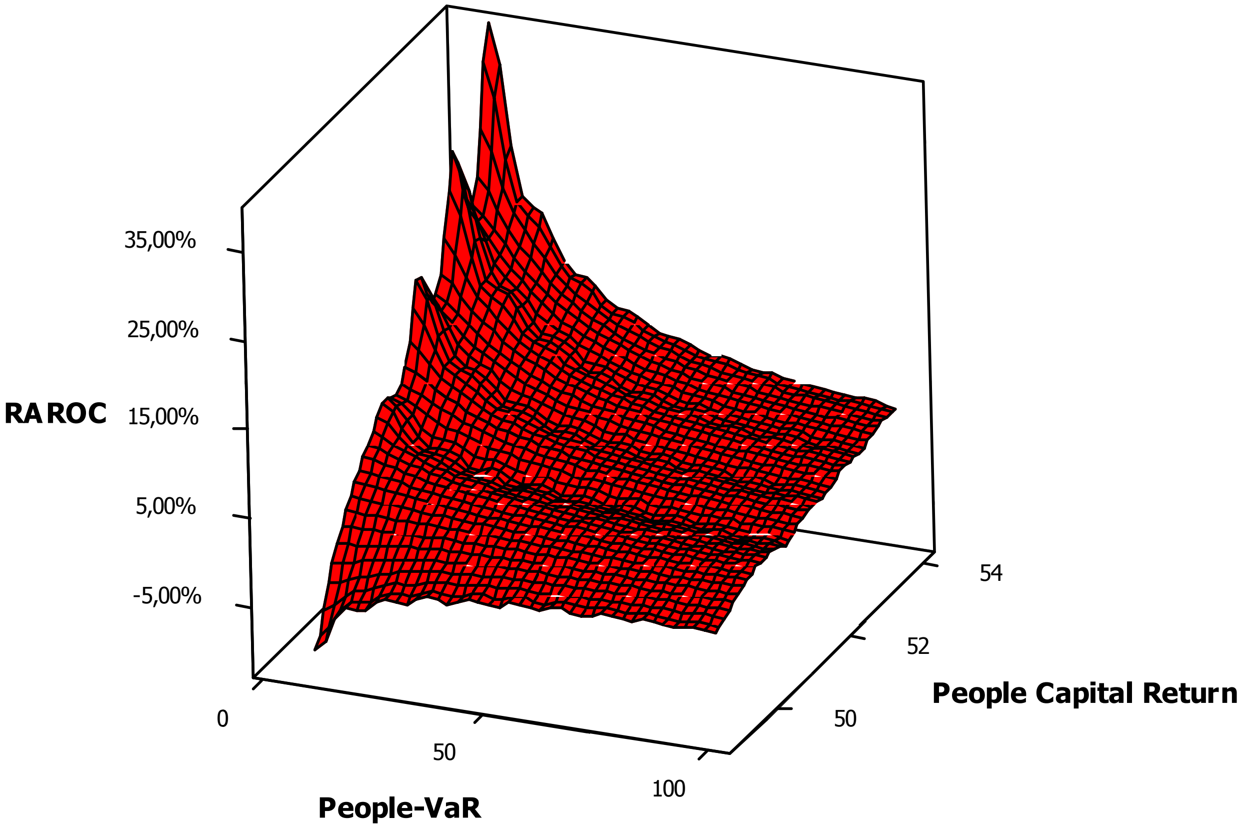
The RAROC (Risk Adjusted Return on Capital) models –explained in section 2 of this paper– provide with sound key-indicators for evaluating a firm's performance. Since the opportunity cost of capital associate to people risk can be estimate by multiplying the return on equity (ROE) and the People-VaR, the value creation arises when RAROC is greater than the minimum required to equity. At this point, we conduct a sensitivity analysis on RAROC depending on the people capital return, ceteris paribus the rest of variables (EL and CaR). Such analysis is carry out for both managerial (95%) and regulatory (99.9%) CaR's, assuming different levels of RAROC for the financial industry.

Table 6: Sensitivity Analysis on RAROC

Event Type	EL	CaR		RAROC	People Capital Return	
		95th	99.9th		95th	99.9th
People-VaR	12.52	18.84	87.48	0.10	14.40	21.27
				0.15	15.34	25.64
				0.20	16.29	30.02
				0.30	18.17	38.76

The results (see Table 6) show the minimum people capital return required for value creation, depending on different RAROC objective values. Moreover, those values are tied to the People-VaR estimation so top managers should monitor this hurdle estimate in order to reduce it as much as possible. Thus, People-VaR provides a measure of the degree of efficiency and performance for sound management. In Figure 6 simulates the relationship among three main variables (People-VaR, RAROC and People Capital Return) at the same time.

Figure 6: Surface chart.



5. Concluding Remarks

People are arguably the most important asset for companies, but they are a source of risk at the same time. Traditionally, they have been overlooked by financial risk managers since people risk is difficult to be measured. It relates to human errors, lack of integrity and honesty, lack of professionalism, insufficient skills, poor training, etc. In fact, people risk lies behind a lot of dramatic episodes causing huge losses for firms. There is urgency for a proactive people risk management to mitigate those *intentional* –with the individual or group being fully aware of their behavior- and *unintentional* –where losses are due to the ignorance, inexperience- events. In this way, the identification and quantification of people risk should be the first step to address it. In this paper, we measure different risk categories (Internal Fraud, Employment Practices and Workplace Safety, Clients, Products and Business Practices and Execution, Delivery & Process Management) that are “people-related”, providing a new key-indicator for managers of financial institutions to improve bank’s risk-adjusted performance. More specifically, we apply the Value at Risk concept as a metric of people risk giving raise to *People-Value at Risk* (People-VaR). Then, this statistical measure is used for estimating the Risk Adjusted Return on Capital (RAROC) as a benchmark for the financial performance. Both measures are useful tools for monitoring the shareholder’s value creation.

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